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LSTM Classification of Functional Grasps using sEMG data from low-cost wearable sensor

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***Abstract* — Modelling human grasping and transferring this data to an anthropomorphic robotic hand to endow it with human like grasping capabilities is a complex task. In this paper the use of surface electromyography (sEMG) for classification of functional grasps associated with everyday life is carried out using a low cost wearable sensor in conjunction with state-of-the-art recurrent neural networks. The results produced through these experiments demonstrate the potential for sEMG to be used as an effective medium for transferring human demonstration to a robotic system.**

Keywords—LSTM, Grasping, Wearable Sensors, sEMG, Signal Classification, Recurrent Neural Networks

I. Introduction

Robotic grasping has been described as being the next big challenge in the development of robotic systems [1]. It is a complex task that has been attempted using both analytic and data driven approaches. Data driven approaches have been identified as providing better performance in robotic grasping when demonstrated using real world experiments [2]–[5]. In order to develop data driven models that control the grasping capabilities of a robotic system, the developed model requires data extracted from real world human demonstrations. In [2] a survey was carried out and highlighted how analytical approaches make assumptions that prior object knowledge is available to robots but they note that this is not always the case. These assumptions and the programmed perfection of simulated environments can lead to less than optimal execution when realised in physical robotic hands/grippers. Many methods of informing a data driven grasping system have been investigated, ranging from using motion capture [6]–[8] to data gloves [4], [9]–[11]. Another method of capturing human biological data when performing grasps associated with activities of daily living is through the use of electromyography (EMG). EMG is the detection of the electrical activity of the muscles used in the body when contracting to perform a particular aspect of movement i.e. Flexor Digitorum Profundus or Extensor Digitorum Communis are the muscles responsible for the extension and flexion movements performed by the fingers. The most appropriate method of EMG detection is achieved by placing electrodes on the surface of the skin above the muscles being targeted and representing these signals digitally to the user. This non-invasive method has been proven to provide equivalent performance to that of the invasive methods of EMG detection which involves placing fine wire needles in the muscle tissue of the subject [12].

sEMG has been implemented in many different models involved with tracking human movements [13]–[16]. These works have used varying types of sEMG detection devices, ranging from expensive medical grade equipment to low cost commercially available sensors. Medical grade equipment generally offers larger sampling rates that can range from 500 Hertz (Hz) – 10000 Hz, but these devices can be expensive and may require help from a medical professional/expert to perform electrode placements [12]. Alternatively, commercially available wearable devices i.e. Myo[1] Gesture control armband, are candidate devices to be implemented in grasp modelling systems. The Myo is an intuitive device that fits around a subjects forearm targeting the Flexor Digitorum Profundus or Extensor Digitorum Communis as well as the other muscles involved in dexterous finger movements. Whilst this device offers a cost effective solution to EMG detection it has a sampling rate of 200 Hz which has been demonstrated to reduce classification performance due to reduced data collected per second e.g. 200 samples/second (200 Hz) vs 2000 samples/second (2000 Hz) by medical grade device [17].

EMG signals have been used extensively throughout the literature especially for gesture recognition [18]–[20]. Recognition of gestures, or in this case grasp postures, can be achieved using contemporary machine learning algorithms i.e. multi-layer perceptron networks or recurrent networks [21]–[23]. The combination of these machine learning techniques together with the benefits of extracting statistical features from the original raw EMG signal have been demonstrated to help improve accuracy of signal classification and make EMG based control of robotic movements possible. Subsequently, the purpose of this research paper is to perform classification of sEMG signals detected using a low cost wearable sensor from a human subject performing grasps on an object using different

[1] https://support.getmyo.com/hc/en-us/articles/203398347-Getting-started-with-your-Myo-armband

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combinations of fingers to secure the object. Furthermore, the diversity of the system is evaluated by attempting to distinguish the same set of grip postures performed on cylindrical objects with a range of diameters.

The rest of the paper is structured as follows: Section II outlines the related work in this field. Section III describes the methodologies used as well as the network architectures and a description of the technology used. Section IV outlines the experimental protocols employed in the experiments that were carried out. Section V reports the results of the experiments and Section VI provides a conclusion and summary of the work detailed. Finally, Section VII details future work that can advance the research further.

II. RELATED wORK

The process of sEMG has been used in research ranging from diagnosing medical issues [16], control of musical devices [24], for control of prostheses [25]–[27] and more recently in the robotics field [28]–[30]. Furthermore, sEMG signal classification has been applied to gesture recognition problems [31]–[34]. Initially the research involved looking at basic movements and gestures i.e. pronation and supination of the forearm and open and closed hand movements [35], [36]. Medical grade equipment was employed, and detection devices with 1000 Hz sampling rate were used to target the Flexor Carpi Radialis and the Extensor Carpi Radialis in the subjects forearm using only one [35] and two [36] pairs of electrodes which were placed directly on the surface of the skin above the muscles. A mixture of time domain and frequency domain features were extracted from the original sEMG signal and [35] trained a neural network to classify this data whereas, [36] trained support vector machines (SVM), linear discriminant analysis (LDA) and multi-layer perceptron (MLP) to classify the signals.

Tenore et al. [37], [38], investigated individual finger movements together with the grouped movements of the middle, ring and little finger. The movements of these fingers are controlled by the same muscle that attaches to the tendons of each of these fingers. Using a large array of 32 electrodes placed uniformly around the circumference of the forearm, with a sampling rate of 2000 Hz, the authors target all of the relevant muscles that contract to cause the dexterous movements of the fingers. Tenore et al. [37], [38], trained a multi-layer perceptron to classify the signals of able bodied and amputee subjects using a small set of time domain features, Mean Absolute Value (MAV), Variance (VAR), waveform length (WL) and Willison's amplitude (WAMP). A similar investigation was conducted in [39] where the authors looked at a selection of individual finger movements and some grouped movements of the coupled fingers i.e. flexion of middle & ring finger or flexion of ring & little finger. Using 6 pairs (12 channels) of electrodes, sampling at 2000 Hz and placed round the circumference of the upper forearm, they extracted EMG signal when the subjects were performing the various movements. From these signals a set of time domain features, known as TD-AR consisting of Autoregressive Model (AR), root mean square (RMS), Waveform Length (WL), Slope Sign Change (SSC), Zero Crossings (ZC) and integrated absolute value (IAV), were extracted using an overlapping window method with window sizes of 200 millisecond (ms) with a 50 ms increment/overlap.

Atzori et al. [19] explored a more comprehensive collection of finger movements, gestures and grasp postures; 50 in total. In this research they used 2 different medical grade collection devices with varying sampling rates. One of the devices, the MyoBock[2], has a sampling rate of 100 Hz and the signal was amplified with a gain of around 14,000. The second device used was a Delsys Trigno[3], this device has a sampling rate of 2000 Hz and was used to record data in two of the three databases created. After the pre-processing and filtering of the raw EMG signal, the next step in the process was to extract statistical features from the filtered signal. Features were extracted that are found in both the time domain and frequency domain. The time domain features included RMS, Histogram and a set of time domain features referred to as the Hudgins Set, as it is a set of features used by [40]. These features are some of the most commonly used in EMG signal classification, MAV, MAV Slope (MAVS), ZC, SSC and WL. The frequency domain feature that was used in this research was marginal discrete wavelet transform (mDWT). mDWT is a frequency feature that ignores the time components of the decomposed signal and preserves only the marginals of each level of decomposition. Using these features, extracted from 200 ms windows of EMG signal, they trained various machine learning algorithms; k-Nearest Neighbours (kNN), SVM and random forests to classify sEMG signals from the fifty different movements performed by subjects.

In [21], a series of dynamic movements were investigated including wrist movements, forearm rotation and some gestures grip postures. The main aim of this paper was to introduce a new dimensionality reduction method which the authors called Orthogonal Fuzzy Neighbourhood Discriminant Analysis (OFNDA). Subjects performed open and closed hand movements as well as a "key grip" and "chuck grip". The authors implemented a bespoke system that used 2 pairs of electrodes placed on the anterior and posterior compartments of the forearm. The electrodes sampled the data at 2048 Hz and from the data sampled during the muscle contractions, a set of time domain features were extracted. In addition to the features already mentioned and found in the TDAR feature set, skewness has been added by the authors. The features in this paper were extracted from windows of 384 samples per window (approx. 187.5 ms) with a 64 sample increment (approx. 31.3 ms) and then used to train an SVM and an MLP classifier.

In [41], the effect of performing grasps at varying arm positions was investigated. The authors implemented fifteen pairs of electrodes, sampled at 2048 Hz, positioned in 2 rings around the forearm. From 250 ms windows of the original signal and a 225 ms overlapped increment a series of features were extracted. The features that were extracted from time and frequency domains. MAV, WL, ZC, SSC and AR from the time

[2] Otto Bock HealthCare GmbH, www. ottobock.com

[3] Delsys, Inc, www.delsys.com

domain were used in addition with standard deviation (SD) and Sample Entrophy (SamEn). Features from the frequency domain were also implemented in this research. The authors calculated the energy of a 4 level Wavelet decomposition (WDC) and a variation of this feature known as energy difference of a 4-level wavelet decomposition (WDCIF). The data collected from the subjects was used to train an SVM. The authors reported the results of the individual features and how the position of the arm affected the final results when the SVM was trained with data from the arm taken in a single position.

Li et al. [42] worked on classification of grasps only. A series of common everyday grasps were performed by the subjects: cylindrical grip, hook grip, lateral pinch, precision tripod, spherical grip and tip pinch grip. Using a single pair of electrodes with a 500 Hz sampling rate the authors were able to successfully classify these grips whilst testing various feature combinations. Time domain features MAV, WL and log variance (LogVar) were used in a set and also in a combinational set with the other features used. Empirical mode decomposition (EMD) with three intrinsic mode functions (IMF) was used to decompose the signal. The mean power frequency (MPF) was calculated from the three IMF bands of the original signal. The various feature sets were used to train a quadratic discriminant analysis (QDA) classifier. On this occasion the time domain set outperformed the frequency domain feature set when classifying the various grasp gestures that had been performed.

The papers reviewed hitherto all used sEMG detection devices with sampling rates of 500 Hz up to 2048 Hz, with the exception of [19] where the authors used a MyoBock system with only 100 Hz sampling rate but they did perform amplification to the original signal with a gain of 14,000. Another feature of the MyoBock system is that in addition to amplification of the signal, it also provides integrated band pass filtering and an RMS rectified version of the raw signal. All these additional factors may help to mitigate the reduced sample rate and improve classification.

Classification of sEMG grasping signals using low cost sensors has been researched to a lesser extent. Various research has been conducted looking at individual finger movements ([18], [43]), but also some common movements i.e. finger point, wrist flexion/extension, open and closed hand [44], [45] with some researchers investigating grasps associated with activities of everyday life. Mendez et al. [46] compared a conventional system i.e. medical grade system (1000 Hz sampling rate), with the Myo gesture control armband (200 Hz sampling rate). A series of movements were recorded ranging from basic wrist extension and flexion as well as key grip pose and pinch grip pose. Using time domain features MAV, WL, WAMP, SSC and ZC extracted from 200ms windows with a 50ms increment/overlap, along with the signal cardinality the authors trained and compared an SVM and LDA classifiers. They found that whilst the conventional system performed better overall the difference in classification error was less than 5%.

Pizzolato et al. [47] provided further comparisons of medical grade EMG devices and the commercially available Myo armband. The authors compared the performance of a single Myo armband with a second that was positioned at a different angle and also in combination with each other. In this work in order to perform a fair comparison with other experiments a total of 41 movements were used out of the 50 movements that were recorded by both able bodied and amputee subjects. The authors extracted a set of time and frequency domain features, identical to those in [19]. The features were extracted from 200 ms windows with a 100 ms increment/overlap and used to train SVM and random forest classifiers for comparison.

Research has been conducted in the realm of gesture classification; however, the gestures performed in these works do not always focus on functional grasping. This research focuses solely on functional grasps and attempts to classify between grasps performed using varying numbers of fingers but also between the same grasps performed on different objects. A range of different sEMG detection devices have been implemented successfully across the reviewed research in conjunction with various classification techniques including devices with a much lower sampling rate than the medical grade equipment that was often utilised. This research will utilise a low cost wearable detection device and using the signal processing techniques highlighted to classify the sEMG signals using state of the art machine learning algorithm.

III. Methodology

This section describes the technology and methodologies being employed in this research and describe each segment of the pipeline demonstrated in Fig 1. Section A describes in detail the technology being used in this research, the Myo gesture control armband. Section B describes the features being used and the process behind their extraction from the original raw signal. Finally, Section C discusses the architecture of the machine learning algorithm used, in this case an LSTM network.

A. sEMG Detection Device

As aforementioned this research revolves around classification of sEMG signals produced by the muscles involved in the control of dexterous finger movements when forming and performing functional grasps associated with activities of daily living. Whilst there are many options available to a researcher these devices vary greatly in many different ways. There are EMG devices that are of medical grade quality that despite offering superior capabilities i.e. sample rates of 2000 Hz+, they can be restrictive to researchers due to their cost and in some cases can require an element of expertise to configure and deploy in a research setting.

In this research a more accessible sEMG device has been used. The commercially available Myo gesture control armband, shown in Fig. 2, is the device being used to detect and extract

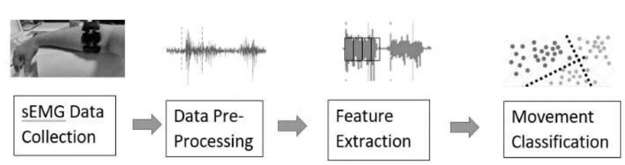


Fig. 1. Abstract view of proposed system architecture

Fig.2: Myo Gesture Control Armband

the subject's EMG signals. This device offers advantages and disadvantages to a researcher. It is an intuitive device that a novice user can operate with no prior knowledge of how it functions. It offers the user an affordable, portable solution to sEMG signal detection.

The Myo is a wireless device, made up of 8 stainless steel dry electrodes that fit uniformly around the forearm of the subject. It also has a built in nine axis inertial measurement unit (IMU) with a three axis gyroscope, three axis accelerometer and a three axis magnetometer that measure the speed of movements and orientation of the armband in 3D space. The electrodes positioned around the forearm detect the inherently weak EMG signal generated when the muscles contract to produce the desired finger movements. The Myo represents these signals in a normalized value range from -128 and 128.

Whilst this device contains all the technology required for detecting and extracting these biological signals produced by a subject, there is a negative element that has been investigated in other research [17]. This drawback is the sample rate, whilst other medical grade equipment can boast sample rates of up to 10,000 Hz for some devices, the Myo gesture band samples at only 200 Hz. This means that the Myo can only detect and represent 200 samples per second which can make the task of classifying these signals much more difficult [17]. Whilst this has been highlighted as an issue it has also been overcome and shown that the Myo still offers enough data to train a neural network to classify various types of signals [18], [43], [47], [48]. Using some tried and tested signal processing techniques i.e. feature extraction, classification can still be carried out with less than 5% difference in accuracy [46].

B. Feature Extraction

When processing a signal for classification it is recognised that the dimensionality of the original raw signal needs to be reduced [49] in order to improve the classification performance of the classifier being employed. One of the most popular methods of reducing the original signal is by performing feature extraction on the signal. Feature extraction is used to extract as much of the useful information found in a sEMG signal whilst removing any unwanted outliers or signal noise. Features can be extracted from 3 main domains: Time, Frequency and time-frequency. Features from all of these domains have been investigated in various pieces of work throughout the literature [40], [43], [49]–[51] with varying degrees of success, with time domain features being the most commonly used. These features have been used as they have been described as the most computationally efficient when being extracted from the original signal but also because they have been demonstrated to improve signal classification performance [49].

In this research a set of 11 commonly found time domain features have been used. As mentioned, this is due to the computation efficiency and the potential improvement of classification accuracy they offer. This is the same set of features that has been used in previous research conducted by the author [43]. The features are displayed in Table 1. For further information on these time domain features please refer to [43], [52].

As with previous research carried out in this field by the author, further established techniques were applied to process the signal and prepare it for use with a machine learning algorithm. A key technique known as overlapping sliding windows is used to increase the amount of information extracted from the original signal. Whilst reducing the dimensionality of a signal is important, reducing it by too much can reduce the signal to a level where it holds no identifiable information and cannot be used by the machine learning algorithm to learn the patterns within the signals. Overlapping sliding windows operate by segmenting the original signal into discrete time windows within the original signal and then overlapping these windows along the original signal by a predefined overlap size [53]. In this research window sizes were set at 200ms with a 25ms overlap. This means the original signal was decreased from its initial 1100 data points per sample down to 213 data points per sample for each feature that is extracted from the signal. Fig. 3 (a) shows the original signal before features were extracted from sliding windows and Fig. 3 (b) shows the MAV representation of the original signal extracted from 200ms windows with an overlap of 25ms.

Table 1: Features Extracted from Original Signal

Feature	Expression	Feature	Expression
Mean Absolute Value (MAV)	$\bar{x_1} = \frac{1}{N}\sum_{k=1}^{N}\lvert x_k\rvert$ for i = 1, ….., I	Willison Amplitude (WAMP)	$\sum_{n=1}^{N-1} f(\lvert X_n - x_{n+1}\rvert)$
Waveform Length (WL)	$WL = \sum_{n=1}^{N-1}\lvert x_{1+1} - x_n\rvert$	Root Mean Square (RMS)	$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2}$
Variance (VAR)	$VAR = \frac{1}{N-1}\sum_{n=1}^{N} x_n 2$	Standard Deviation (STD)	$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^{\,2}}$
Autoregressive Modelling (AR)	$X_k = \sum_{i=1}^{\rho} a_i X_{k-i} + e_k$	Mean Absolute Deviation (MAD)	$MAD = \frac{1}{N}\sum_{i=1}^{n}\lvert x_i - m(X)\rvert$
Kurtosis (KURT)	$Kurt = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^4}{(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2)^2}$		
Slope Sign Change (SSC)	$SSC = \sum_{\Pi=2}^{N-1}[f[(x_n - x_{n-1})x(x_n - x_{n+1})]]$		
Zero Crossings (ZC)	$ZC = \sum_{n=1}^{N-1}[sgn(x_n * x_{n+1}) \cap \lvert x_n - x_{n+1}\rvert \geq threshold]$		

C. *LSTM Network & Architecture*

Recurrent neural networks (RNN) are a class of neural networks that have been previously applied in areas of handwriting and speech recognition [54]–[56], anomaly detection [57] and learning from time series information [58]. An LSTM network is a RNN that was developed to mitigate against the vanishing gradient problem suffered by neural networks that implement a gradient based learning method or backpropagation [59]. The application of the LSTM network has been demonstrated in studies investigating classification of human movements [60] and in the field of robotic control [61]. Moreover, it has been implemented successfully in biological signal classification systems [43]. An LSTM network specialises in classification of sequential data and prediction of future steps in sequential data which is down to its ability to enforce constant error flow between its special units' internal states. This functionality removes the problem associated with other RNN's where the gradient can explode exponentially or vanish. Previous work conducted has demonstrated how LSTM can accurately classify signals generated by the electrical activity of the forearm muscles when performing dexterous movements of the fingers and thumb [43].

In this paper, the LSTM network was applied to classification of signals generated when performing a series of functional grasps associated with activities of daily living i.e. pinch grip, power grasp.

The architecture of the network applied in this paper is shown in Fig. 4. This architecture has been used in previous work [43] and has shown to perform classification of EMG signals with relatively high levels of accuracy.

IV. DATA COLLECTION & MOVEMENTS

This section will outline the protocols followed during the data collection process, the movements that were performed and finally the results of the carried out experiments.

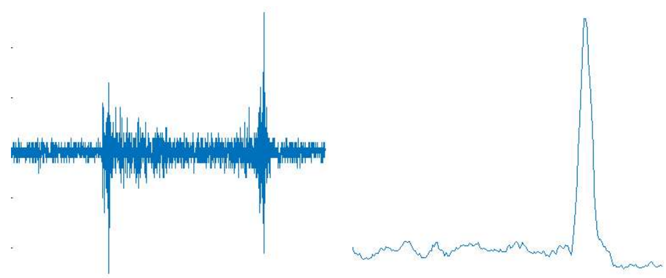
A. *Data Collection*

Data was collected for this experiment whilst the subject was performing functional grasps associated with activities of daily living. As highlighted by the literature review, work has been carried out in this field but this experiment focuses solely on functional grasps opposed to basic hand gestures and individual finger movements that has been investigated in other research [38], [43], [48], [52]. The data was collected for this experiment in accordance with the protocols set out in [43]. The only variation on this protocol was that the subject had an object to form a grasp around so as to gather data on a functional grasp that was being performed on a real object. The Myo armband was fitted around the subjects forearm following Thalmic Labs[4] guidance on properly positioning the device. The subject then performed 70 repetitions of the each grasp to be performed in this experiment. The EMG signals were detected by the Myo and using a specifically designed Matlab[5] toolbox [62], each sample was recorded. The samples were split randomly into two groups, 72% (453 samples) for training and 28% (189 samples) for testing.

B. *Functional Grasps & Objects*

The grasps performed ranged from five fingered power grasp to a two fingered pinch grip. These grasps are acknowledged by [63] as grasps associated with activities of every daily life. The grasps were then performed on two different objects with different diameters. The objective of the experiment is to determine if the different grasps can be distinguished from each other but also if they can be distinguished when they are being performed on every day household objects with considerably different diameters. Fig. 5(a) below shows the different grasps performed.

The objects used in this experiment were objects that have varying diameters. These objects were a large glass (Object 1) with a diameter of 78 mm and a thin metal bar (Object 2) with a diameter of 5mm, as shown in Fig. 5(b). This object was used to represent thin objects that are often found in the house e.g. pencil, spoon etc. The objectives of the experiments carried out in this research are to not only attempt to distinguish between functional grasps involving varying numbers of fingers but also to determine if these grasps can be distinguished when performed on different objects with varying diameters. Following a similar procedure to that in [43]; 30 LSTM networks were trained for each iteration on the architecture. This means that 30 networks were trained when using 10 hidden units in the bi-LSTM layer and another 30 were trained when using 20 hidden units. This procedure was followed until the classification accuracy began to deteriorate or plateau. As mentioned in Section III.C the LSTM network weights are initialised using the Glorot algorithm [64]. This means that each of the 30 networks are initialised with a differing set of weights each time a new network is trained so gathering the average



(a) (b)

Fig.3: (a) Original EMG Signal (b) MAV Feature extracted from original signal from 200ms windows/25ms overlap

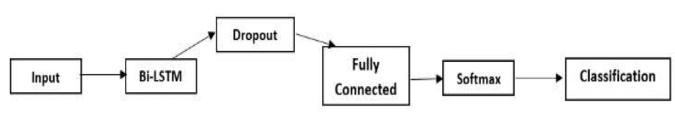


Fig.4: LSTM Network Architecture

[4] www.bynorth.com

[5] https://uk.mathworks.com/

(a) (b)

Fig. 5: (a) Functional Grasps (Top row from Left to Right) Power Grasp, Pinch Grip, Tripod Grip, Quad Grip. (Bottom Row from Left to Right) Power Grasp, Pinch Grip, Tripod Grip, Quad Grip. (b) Objects used Object 2 (5mm diameter), Object 1 (78mm diameter)

results provides a more balanced view of the results produced as a whole rather than on a singular network basis.

V. Experiment & Results

A series of networks were trained to classify a differing number of functional grasps and the results will be displayed and discussed in this section. All of the networks were configured using the same set of parameters so that a fair comparison can be drawn between all the trained networks. Table 2 shows the LSTM parameters that were used in each of the trained networks.

Table 2: LSTM Network Parameters

Epoch	Mini Batch Size	Dropout	Optimizer	Normalization	Weight
25	56	0.3	ADAM	ZSCORE	GLOROT

A. Experiment 1 – Object 1 Functional Grasps

The first experiment conducted was to investigate if sEMG signals generated by performing various different grasps can be classified accurately using an LSTM network. A network was trained to classify between 6 classes of grasps i.e. power grasp (using all fingers and thumb), pinch grip (thumb and index finger), tripod grip (thumb, index and middle finger), quad grip (thumb, index, middle and ring finger), refer to Fig 4 (a), being carried out on object 1. A further class which contained all the other moves, in this case all the same grasps performed on Object 2 and a rest class. The best performing network architecture achieved an average classification accuracy of 99.81%. This average classification accuracy was achieved when there was 60 hidden units in the bi-LSTM layer of LSTM network, as shown in Fig. 6. A classification accuracy of 100% was attained in some individual networks in all iterations of the network. All of the movements were classified with 100% accuracy across the 30 trained networks with 60 hidden units except for the Tripod grasp which was confused with the all other moves class but only 2% (5 occasions) of all occurrences, shown in Fig. 7.

B. Experiment 2 – Object 2 Functional grasps

The second experiment focused on the same grasps that were performed in the previous experiment but on Object 2. As aforementioned, this object has a distinctly smaller diameter and the aim of the experiment was to determine if these signals, despite using the same number of fingers, can be classified when applied to an object that requires more flexion of the fingers and thumb. The best performing network architecture for this purpose achieved an average classification accuracy of 99.81%. The best performance was attained when using 100 hidden units in the bi-LSTM layer, highlighted in Fig. 8. As shown in Fig. 9,

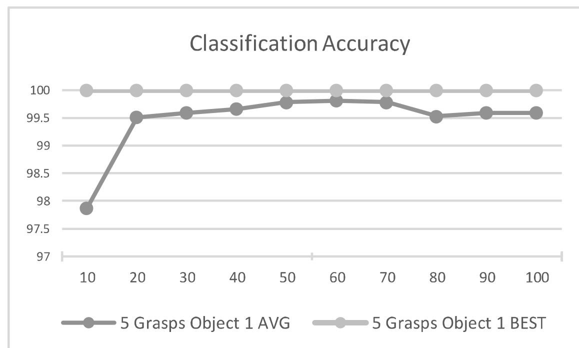


Fig. 6: Average & Best LSTM Classification Results for grasps performed on Object 1

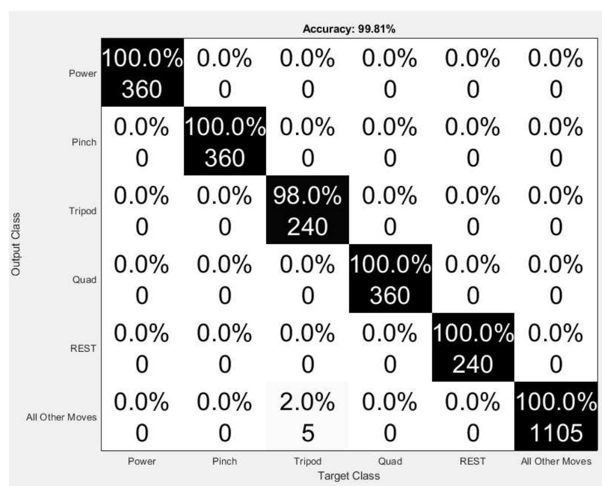


Fig.7: Confusion matrix for combined results of 30 LSTM networks trained with 60 hidden units

confusion was demonstrated when attempting to classify tripod grip. Tripod grasps were classified with 98% accuracy and demonstrated confusion with the all other movements class 2% (5 occasions). This is consistent with the results attained in experiment 1.

C. *Experiment 3 – Combined Functional Grasps on Object 1 & 2*

This experiment combined the gestures carried out on the different objects in a single LSTM classification network. Feature vectors representing each of the gestures performed on the objects were used to train the LSTM network. The LSTM network classification accuracy peaked with an average of 99.03% when using 120 hidden units in the bi-LSTM layer. However, there were multiple networks that achieved 100% classification using as little as 50 hidden units in the bi-LSTM layer. Fig. 10, shows the overall results for the LSTM networks that were trained.

Fig. 11 shows a confusion matrix displaying the combined average results for the individual functional grasps across the 30 trained LSTM networks when using 120 hidden units. In these networks there was very little confusion between the grasps and between the same grasps on objects 1 and 2. The pinch and tripod grasp on object 1 were classified with 100% accuracy. However, there was minimal confusion between some of the grasps performed on the same object. For instance, the 5-finger power grasp on object 1 was confused with the tripod grasp 4.3% (12 occasions) of the time. The power grasp on object 2 achieved 100% (270 occasions) along with the quad grip (210 occasions) on object 2. Pinch grip on object 2 demonstrated the highest amount of confusion of any of the grasps with 94.2% (180 occasions) classification accuracy. This grasp was confused with tripod grasp on object 2, 5.8% (11 occasions) of the time. Not only are these classifications accuracies very high and outperform other methods; the LSTM network also performs classification in a time efficient manner. Classification was performed on a test sample on average 0.280 seconds (s) from 10 trials of the best performing network with 120 hidden units.

VI. Conclusion

Despite reported drawbacks of using wearable sEMG sensor with low sampling rates this paper demonstrates that when using the data extracted during functional grasp demonstration relatively high accuracies can be achieved. In this paper the classification of functional grasps associated with activities of everyday life carried out on objects with varying diameters was performed. When classifying a series of functional grasps on these 2 diametric objects average classification peaked at 99.81% across 30 LSTM networks. This accuracy was achieved when using 100 hidden units in the bi-LSTM layer. The confusion found in the various networks could be caused by issues with class separation between the samples used when training these networks. This can be due to the previously discussed sampling issue with the Myo but also an example of

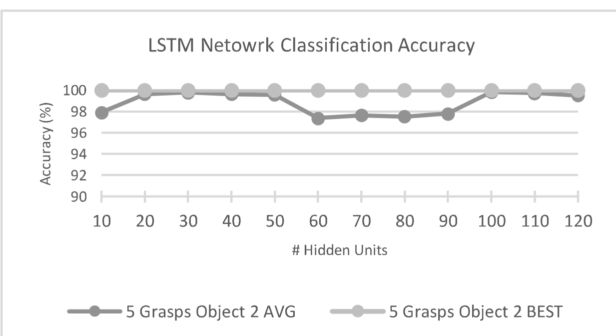


Fig.8: Average & Best LSTM Classification Results for grasps performed on Object 2

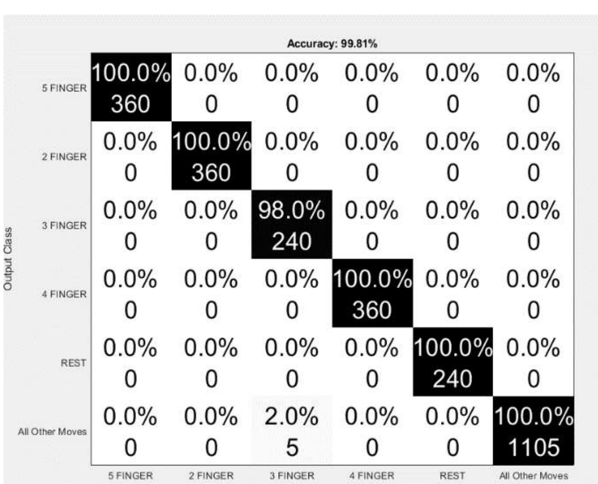


Fig. 9: Confusion Matrix showing combined results of 30 trained networks with 100 hidden units in Bi-LSTM layer

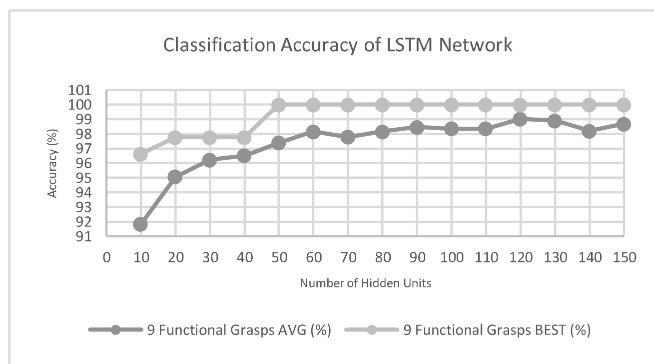


Fig.10: Average & Best LSTM Classification Results for grasps performed on Object 1

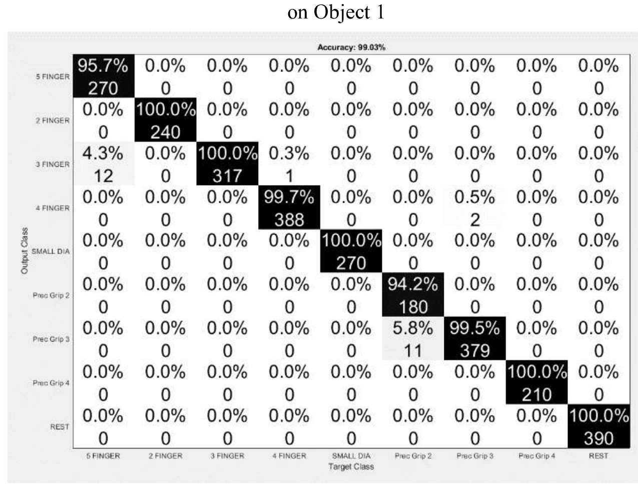


Fig. 11: Confusion matrix for combined results of 30 LSTM networks trained with 60 hidden units

the issue regarding coupling of the fingers. The issue of the reduced sampling rate can explain the lack of class separation due to reduced amount of data samples per demonstration. Furthermore, it can also be hard to decipher how many fingers are moving as some of the tendons share the same muscle therefore similar activity can be detected when attempting move any of the coupled fingers.

As discussed in Section V, an average classification time of 0.280 seconds was achieved when classifying a single test sample. This time is below the recommended upper limit of 300 ms by [65]. Further analysis and testing will be conducted to investigate possible improvements to this time as this aspect of the experimentation was out of the scope of this research.

In this research it has been demonstrated that sEMG signal classification using a low-cost wearable sensor can be used to model human grasps that involve the engagement of the same grouped movements of the fingers but end with very different finishing poses when grasping different objects. Using the model generated from the training of the LSTM networks, it is hoped that it will be possible for the grasps to be recreated using an anthropomorphic robotic hand.

VII. Future Work

Further research will include the addition of more objects with varying diameters, investigation into removing redundant features and more experimentation evaluating the parameters used in the LSTM network e.g. batch size, validation, window size etc. More investigation into the time complexity of the complete system will be conducted in an attempt to reduce the computation time of the process. A further stage in this research will be to apply the generated models to an anthropomorphic robotic hand and successfully grasp objects using human generated grasping data.

VIII. References

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